

Trajectory Planning for Feature-Based Localisation and Mapping

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of the requirements for the degree of
Doctor of Philosophy



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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

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Signature of Student

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Abstract

Localisation and mapping are two fundamental tasks required for many autonomous mobile robot applications. Robot motion has a significant impact on the quality of the outcomes of any localisation and mapping algorithm due to the fact that the information acquired through observing the environment depends on the viewpoint from which the observations are made. This thesis develops mobile robot trajectory planning strategies that maximise the information gain, thereby leading to more effective localisation and mapping outcomes.

In this thesis, the trajectory planning problems are formulated as optimal control problems where the control objective is to maximise the information gain or to minimise the uncertainty of the robot location and/or the map estimate. As not all the information can be predicted before observations are made, the optimal control problems involve gradually identified models. Model Predictive Control (MPC) is proposed to solve the control problems as it exploits updated information in the planning at each time step. Two optimisation strategies are implemented in the multi-step optimization of MPC planning. The first is an Exhaustive Expansion Tree Search (EETS) and the second combines this search with Sequential Quadratic Programming (SQP). Analyses of the results show that EETS provides a near optimal solution.

Three trajectory planning problems are considered. The first problem is trajectory planning for multiple robots in the task of target localisation. The robots are equipped with bearing-only sensors and their locations are assumed to be provided by an external source. Given initial location estimates with large uncertainty, the task is to pinpoint the locations of multiple targets within a prescribed terminal time. An Extended Information Filter (EIF) is used to estimate the locations of the targets.

The second trajectory planning problem considers the task of point feature based Simultaneous Localisation and Mapping (SLAM) for a single robot. Here, the robot is to map a given area within a prescribed terminal time. An Extended Kalman Filter (EKF) is used to estimate the robot pose and feature locations. The final trajectory planning problem extends the SLAM problem further to the mapping of line features. As simply applying EKF to line-feature SLAM produces inconsistent estimates, a Smoothing and Mapping (SAM) algorithm is used as a viable alternative.

In these SLAM problems, coverage is another important performance index. As MPC with a few steps look-ahead is predominately a local planner without any long term planning or any explicit strategy for exploration, an attractor-based strategy is developed to improve its performance. With the addition of the attractor, coverage is shown to be much improved. On a Pioneer2DX robot, real-time line-feature localisation and mapping with SAM is demonstrated.

Nomenclature

Commonly used symbols in this thesis are listed as follows.

$\lambda, \hat{\lambda}$	Target or feature location, target or feature location estimate
$j = 1 \dots J$	Number of features
$i = 1 \dots T$	Update time steps
$k = 1 \dots K$	Number of observations
D, N_ω	Planning horizon, number of discrete control options
$h(.)$	Observation model
$f(.)$	Process model
r, θ, φ	Range, bearing, elevation measurement
α, d	Angle and distance of line measurement
$\hat{\zeta}_i, \hat{\Theta}$	EKF state vector, SAM state vector
Σ_k	Covariance of observation
$w_x,$	Single step process noise
w_z	Observation noise
P_w, Λ_i	Covariance of process noise (single step, multiple steps)
u_i	Controls inputs
v, ω, ψ	Velocity, turnrate, roll
Ω	Array of line segments
μ_{i+1}	Innovation
I	Information matrix
P	Covariance matrix
K	Kalman gain
S	Innovation covariance
β	Mahanalobis distance